Line length: An efficient feature for seizure onset detection

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Abstract-**A signal feature with low computational burden is presented as an efficient tool for seizure onset detection. The feature was evaluated over a total of 1,215 hours of intracranial EEG signal from 10 patients. Results confirmed this feature as being useful for seizure onset detection yielding an average delay of 4.1 seconds, 0.051 false positives per hour, and one false negative on a subclinical seizure out of 111 seizures analyzed of which 23 were subclinical.**
***Keywords* – seizure detection, fractal dimension.**

I. Introduction

There is a lot of undergoing research on seizure onset detection. Osorio and Frei [1], Qu and Gotman [2], introduced some of the many features proposed for seizure onset detection. The first authors developed a feature based on a wavelet FIR filter. They selected the wavelet scale corresponding to approximately 5-40 Hz, squared it and median filtered the output, and finally compared it with a background signal. Their system accomplished zero false positives, zero false negatives, and 2.1 seconds of electrographic onset detection delay on evaluation over 55.5 hours of intracranial EEG data. The second ones designed an intelligent system that extracts six features from the time and frequency domains, three features based on half waves of the input data (average half wave duration, amplitude, and coefficient of variation of the wave duration), a dominant frequency, an average power, and feature containing spatial information. They fed these features into a modified nearest-neighbor classifier, and obtained a 100% detection rate with an onset detection delay of 9.35 seconds, and an average of 0.02 false positives per hour over a total of approximately 32 hours of data analyzed. Many of their features were "features of features" or historical features as denoted in [3].

Among the large number of features proposed for seizure onset detection, we are proposing the line length as an efficient feature for seizure onset detection. This feature was originally introduced by Olsen [4], and later referred to as curve length in [3]. This feature can be derived from the fractal dimension by Katz [5] studied in [6]-[7]; however, unlike fractal dimension is computationally more efficient and more accurate for seizure onset detection.

II. From Katz's Fractal Dimension to Line Length

The fractal dimension as defined by Katz [3], [5]-[6] before the normalization is given by,

$$D = \frac{\log_{10}(L)}{\log_{10}(d)} \tag{1}$$

where L is the total length of the curve or sum of distances between successive points, computed as

$$L = \sum_{i=1}^{N} abs\left[x(k-1) - x(k)\right] \tag{2}$$

and d is the diameter estimated as the distance between the first point of the sequence and the point of the sequence that provides the farthest distance.

Using the normalization that Katz defined in [4] leads expression (1) to

$$D = \frac{\log_{10}(N)}{\log_{10}(\frac{d}{L}) + \log_{10}(N)} \tag{3}$$

where N is the number of points within the window or window length. Using the running window method described in [6] a sequence of fractal dimension values can be generated as a

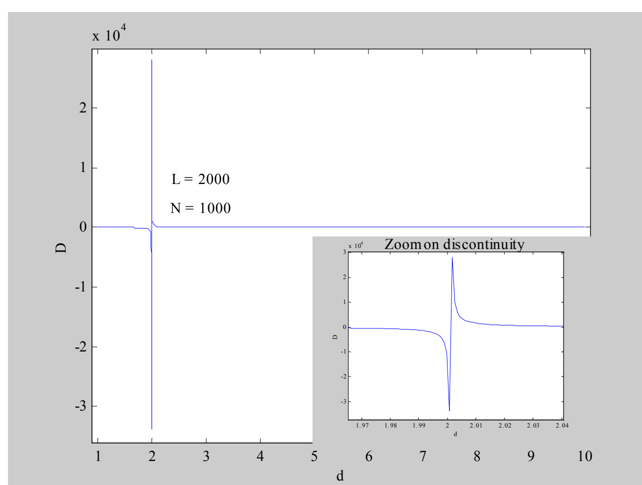

Figure 1: Variation of the fractal dimension by Katz's method as the parameter d is changed

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sliding window moves through the intracranial EEG (IEEG) data. For each window L and d are computed to obtain a value of D. However, analyzing the variation of (1) and/or (3) with respect to parameters d, L, and N, it can be shown that within the broad range of possible values for these parameters, there are combinations of them where Katz definition leads to inconsistencies such as the singularity illustrated in Fig. 1 when plotting (3) as a function of d. Similarly, signals that lead to these fractal dimension inconsistencies can be constructed such as the one shown in Fig. 2, that can be generated with the sequence $x(n) = (-1)^n \, 2 \sqrt{200^2 - (n-100)^2}$, and whose fractal dimension is –16.97 when using (3).

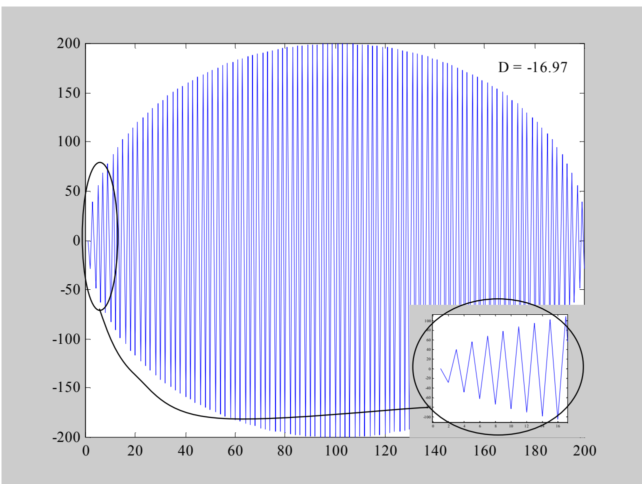

Figure 2: Sequence $(-1)^n \, 2 \sqrt{200^2 - (n-100)^2}$, whose fractal dimension yields a negative value

The results presented in [7] with simulated and experimental IEEG data were within the range of values for which the fractal dimension by Katz works well. Aimed at overcoming this problem and making an algorithm computationally more efficient, we observed that the logarithm functions in (1) and/or (3) could be dropped without affecting the detection capabilities and producing a more efficient feature, in the sense that it becomes faster and numerically more stable. After eliminating the logarithms in the numerator and denominator of (1) and (3), they become L/d. The variable d can be considered as a normalization factor that is updated with every shifting of the sliding window. We have experimentally observed that the value of d does not change much over time and decided to change it into a normalization constant K, that is the number of window shiftings that fit into the sliding window length. This is equivalent to stating that K is the number of times the feature is updated during a time span equal to the running window length (N). Therefore K will make sense only when the sliding window shifting is lower or equal to the sliding window length N. This is the feature defined as line length, where L is the same defined in (2). The sequence of values generated with (2) as the sliding window moves through the data can be represented as in [4] by,

$$LL(n) = \frac{1}{K} \sum_{k=n-N}^{n} abs\left[x(k-1) - x(k)\right] = \frac{L(n)}{K} \quad (4)$$

where $LL(n)$ is the normalized line length value at discrete time index n, $L(n)$ is the running sum of distances between successive points within the sliding window of size N, $x[k]$ is the data sequence value at the k^{th} sample, K is the normalization constant, N is the sliding window length, and *abs* stands for absolute value.

The summation indexes in (4) were changed with respect to the ones of the curve length in [5] to have a causal expression, and the normalization constant K has been added. Note that the line length grows as the data sequence magnitude or frequency increases; in this sense the line length can operate as an amplitude and frequency demodulator. We verified perfect demodulation using test sinusoids with constant and linear chirp frequencies. This seems to be a good property of any useful feature for seizure detection, Osorio and Frei feature in [1] combined time and frequency information, and similarly Gotman's half wave algorithm [2] considers the amplitude and frequency of the data signal.

This study built on the idea in [5] of computing a feature for two different window lengths, a short-term window and a long-term window, such that when the short-term feature goes above or below the adaptive threshold obtained from the long-term feature the detection can be declared. Following this approach, a line length trend is defined as a trend window consisting of sampled intervals whose length is a multiple of the shifting time. Figure 2 indicates how this line length long term window or trend is defined for a portion of IEEG data. Note that instead of using all the points within the long term window, only the regions denoted as data segments in Fig. 2 are the ones considered for the line length trend. This is equivalent to sample the long term window instead of using all of it, yielding computational savings in time and memory. The line length feature as stated in (4) is computed for each data segment of length N within the long term window, and then, the average of all these line length values from every data segment is calculated and defined as the trend value. Figure 3 illustrates how the trend is determined. In this figure, the long term window consists of four sample intervals. Note that the number of sample intervals within the long term window is a patient-specific tunable parameter. In the present study the length of the data segments within the long term window was identical to the length of the running short term line length window defined in (4).

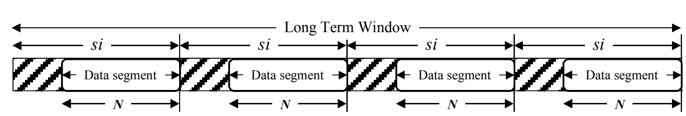

Figure 3: Line length trend window

Seizure onset detection is declared when the running short term line length reaches or goes above a threshold defined as the trend value plus a fixed or percent offset. This offset is another parameter that is tuned to each patient.

III. METHODS

The IEEG data used in the analysis is part of a Georgia Tech - Emory Univ. - Univ. of Pennsylvania database, acquired from epileptic patients that underwent a pre-surgical evaluation and whose IEEG signals were recorded during that evaluation with simultaneous video-taping of the patient activity for a period of approximately 4 to 11 net days (5 to 23 days in the hospital). The IEEG data was 12 bit acquired at 200Hz, but since this study was conducted as part of a validation for an implantable device under development [8], in order to follow closely the operating conditions of the device, the IEEG was reformatted to 10 bits and 250Hz.

Two classes are defined in this study, the seizure-onset class and the non-seizure-onset class. Among the line length parameters, the line length threshold offset (threshold = trend value + offset) was tuned to each patient. To accomplish this, an interactive Matlab toolbox was developed and a training set was established including IEEG from the two classes defined. The Matlab toolbox comprises a library with the line length feature and related codes, a system simulation interface that presents graphs with the input data, line length feature, line length trend, detection output, and performance metrics regarding point basis statistics of the detection output and block basis statistics depending on the class the IEEG segment belongs to. The metrics provided by the system are the FPs, FNs, correct positives, correct negatives, detection delay for each seizure, and average detection delay for a patient group of seizure. On this training set a manual tuning was performed to determine the threshold that yielded the best results. A desired goal was pre-established as no more than 10% of false negatives (FNs) and less than two false positives (FPs) per day (0.0833 FPh). The training records were defined as 3-minute segments clipped from the database. Training records from the seizure-onset class were clipped such that there were available two-minutes of preictal period and 1-minute of ictal. The number of seizure-onset records within the training sets of each patient varied between zero and nineteen. Patient *j* used 19 seizure-onset training records; she had a total of 31 seizures available including 22 subclinical seizures. Patient *e* used zero records because before starting the manual tuning his training set worked at the very first try with the set of parameters used in patient *b*'s parameters used as default, therefore no tuning was necessary for this patient. The number of non-seizure-onset records within the training sets varied between 1 and 15. A total of 68 seizure-onset and 86 no seizure-onset records were used for training leaving for testing a total of 43 seizures and 1205.15 hours of non-seizure-onset class. The testing set of each patient was not used during the patient tuning of line length p, it was only utilized at the end to validate the proposed feature. After the manual tuning of the threshold offset in each patient, the line length detection tool was run over the entire hospitalization stage available for each patient.

IV. RESULTS

Table 1 presents the results obtained after computing the line length feature over 1,215 hours of intracranial EEG available from 10 patients analyzed.

Table No. 1: Line length detection results

Patient	FPh	FNs	ADEO Delay	# Hours Analyzed
a	0.111	0	9.26	45.0
b	0.087	0	-3.44	46.2
c	0.083	0	7.15	204.3
d	0.052	0	1.79	38.7
e	0.000	0	0.32	65.4
f	0.000	0	2.73	156.0
g	0.076	0	8.65	39.3
h	0.081	0	6.89	197.3
I	0.004	0	4.25	269.0
j	0.013	1	3.37	153.8
Average	0.051	0.1	4.10	1215.0

FPh: False positives per hour.
FNs: False negatives
ADEO Delay: delay of the detection time with respect to the unequivocal electrographic onset in seconds.
CO Delay: Clinical onset time with respect to the detection time in seconds.

V. DISCUSSION AND CONCLUSIONS

Considering the fact that only one feature was used in this study, the results are very encouraging. If other efficient features of different nature, are added into the system, then better performance is expected due to the complementary effect obtained when efficient features are combined together [2],[3],[9]. In addition this feature is suitable to be used in any other areas were the primary goal is detection of a signal event. Further research in underway to study the performance of this feature in combination with others.

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